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Weed Sensing - Where Are We?

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INTRODUCTION

Recognition of the potential benefits of being able to variably apply herbicides based on the sensing of weeds has led to much research and development activity. The purpose of this paper is to survey what work has been done already with a view of formulating future research and development directions with a goal of the development of practical weed sensing technology. Two approaches have typically been used for weed detection. The first is the photo-detection approach, which measures the average reflected light from the field of view of the detector. Light-detecting (photo) diodes or resistors have been used in this low resolution approach meaning that the area sensed by one sensor is large. The other approach is the machine vision approach. In this approach, digital images of the field scene are acquired with some type of camera, and the information contained in these images is processed by a computer to retrieve knowledge or understanding of the scene. Examples of both of these approaches will be discussed in this paper.

MOTIVATION: UNIFORM TREATMENT IN THE PRESENCE OF AGGREGATION

Large amounts of pesticides are applied each year to the fields of U.S. farmers. In 1995, about 939 million pounds of pesticides were used in agriculture (Aspelin, 1997). In 1997, $8.8 billion was spent on pesticides which represents a 3.5 percent increase over the $8.5 billion expenditure level of 1996. Herbicides account for 65 to 70 percent of these pesticides (Economic Research Service, 1997, 1998). Hence, herbicides represent a costly input to field crop production, are a source of environmental concern, and are relied on heavily for effective weed control to minimize yield loss in crop production.

Typically, herbicides are applied uniformly to a whole field without regard to the spatial variability of the weeds in the field, although research has shown that weed aggregation exists (Marshall, 1988; Wilson and Brain, 1991; Thornton et al., 1990; Wiles et al., 1992; Cardina et al., 1995; Mortensen et al., 1993). This practice results in some areas where no or few weeds exist receiving just as much herbicide as those areas with high densities of weeds. If a more sophisticated chemical application control system were developed which applied herbicides in a spatially varying manner based on weed density, a reduction in herbicide usage would occur (Mortensen et al., 1995; Johnson et al., 1995). This practice would result in lower environmental loading and increased profitability in the agricultural production sector.

Site-specific weed management and integrated weed management have been proposed as practices which use knowledge of weed variability to achieve economic and environmental goals (Mortensen et al., 1998; Lindquist et al., 1998). Integrated weed management is based on the principles of integrated pest management (IPM) which seeks to lower pest density to levels which are "acceptable" through a variety of methods (Barrett and Witt, 1987). To implement site-specific weed management and integrated weed management practices, it is therefore necessary to estimate the weed density (numbers of plants per unit area) or weed population as a function of location in crop fields. Because manual sampling is both laborious and costly, it would be difficult to implement these management systems on a crop production scale. However, if an automated system were developed which sensed and estimated the local characteristics of weeds, weed management systems which used this information would be feasible from a data collection point of view. Such an automated system could be used in two different ways. It could first be used for real-time local sensor-based variable or intermittent herbicide application where the herbicide is applied based on the sensing of local conditions during application. The second way this type of system could be used would be to generate GIS-based maps of the weed characteristics. These maps could then later be used for variable rate herbicide application. Such a system would need to process a large amount of data in real-time and to be robust to the variability associated with outdoor lighting conditions while meeting goals of both reliable and economical operation.

A successful weed sensing system would need to be able to retrieve weed information from a highly unstructured and variable environment. This is a challenging technical task which can be divided into several sub-tasks. First, the weed sensing system must be able to detect vegetation in the presence of variable lighting conditions. Second, the weed vegetation must be discriminated from the crop vegetation. Third, for variable-rate herbicide application or map generation, local weed infestation characteristics must be estimated. In addition, if the system is to be used for a sprayer which applies herbicides in a variable rate fashion based on local sensor-based weed detection, there must be some method of deciding the application rate based on local conditions, and the actuation of the nozzle must be synchronized with the location where the weed was sensed. The work that has been done in each of these sub-tasks will be described below.

VEGETATION DETECTION

The baseline operation that a successful weed sensing unit must accomplish is to detect vegetation by discriminating between the vegetation and the residue or soil. This is done based on differences in the spectral reflectance of the vegetation as compared with soil and residue.

When light energy impinges on an object, part of the light energy is absorbed by the object, part of it is transmitted through the object, and part of it is reflected by the object. The fraction of the incoming light reflected by the object is determined by the material properties of the object and is thus called the reflectance of the object. In general, the reflectance of an object varies across the visible spectrum which results in the perceived color of objects. Thus an object that appears green in color has a higher reflectance in the part of the visible spectrum that humans perceive as green than in other parts of the spectrum.

Vegetation detection uses the fact that the reflectance of plants is substantially different than that of other objects in the crop field. Plants have a relative low reflectance – approximately ten percent – in the visible spectrum with a slightly larger reflectance in the green region of the visible spectrum giving plants their green color. This low reflectance exists because of the high absorption by chlorophyll pigments. In near infrared (NIR) region, that region of light which is invisible to the human at wavelengths from about 720 nanometers (nm) to 1300 nm, the reflectance is markedly larger and relatively constant. At wavelengths above 1300 nm, the reflectance decreases with several "valleys" caused by water absorption (Knipling, 1970; Woolley, 1971; Swain and Davis, 1978).

Soil and residue on the other hand, do not have this sharp increase in NIR reflectance that is characteristic of vegetation. The reflectance of soils is typically an increasing, relatively linear function of wavelength across the visible and NIR regions of the spectrum and typically less than 20 percent. In addition, crop residue reflectance is a linear function of wavelength but increasing to approximately 40 percent in the NIR region (Nitsch et al., 1991). Thus if the magnitude of broadband NIR reflectance alone is used for vegetation detection, residue will be incorrectly considered to be vegetation.

Photo-Detection Approach

Ratios of the reflectance magnitude of bands in the visible and NIR regions have been used for vegetation detection since a sharp discontinuity between the visible and NIR reflectance exists in vegetation and not in soil or residue. These ratios are used in photo-detector-based vegetation detection systems which were the first vegetation detection technology to be developed. Hooper et al. (1976) developed a photo-detector-based sensor which electronically measured a ratio of visible light (400 to

700 nm) to NIR (700 to 1000 nm) light to distinguish between plants and soil. This sensor was able to distinguish between plants and soil, but encountered some problems with variations in sunlight intensity. Hagger et al. (1983) described a similar device, called a reflectance ratio meter (RRM), which used a ratio of red to NIR light for vegetation detection. The RRM was used to control a handheld patch sprayer. The performance of the sensor was measured indirectly based on the performance of the sprayer. The amount of herbicide applied with this sprayer was highly correlated with the total patch area of grass, and about 90 percent of the grass was killed. The use of this sensor to control a patch sprayer resulted in an estimated 60 percent reduction in herbicide when compared with uniform application.

Shropshire et al. (1990) described the development of a RRM which used a ratio of red and NIR light reflected from the field surface. The accuracy of a RRM was tested. The output of the RRM was correlated with the plant population with a 0.8 to 0.9 coefficient of determination, depending on the day the experiment was run. When the sensor was mounted at 0.45 m above the soil surface, the sensor field of view was estimated to have a radius between 0.05 m and 0.10 m. This sensor was revealed to be sensitive to changes in illumination. Von Bargen et al. (1992) described a sensor which used a vegetative index as a means of avoiding sensitivity to lighting changes. By sensing the reflectance in different spectral bands, particularly the red and NIR bands, ratios can be formed which typically have significantly different values for living plants and soil or residue. These ratios are called vegetative indices and are metrics computed from the magnitude of the reflectance of different spectral bands and have been a standard tool of the remote sensing field (National Research Council, 1997).

There are at least two commercially-available selective sprayers on the market today, both of which use photo-detector RRM for weed sensing. The Detectspray system (Concord, Inc., Fargo, ND) uses light detecting diodes with red and near-IR bandpass filters to detect the average reflected intensity of the light in these bands in the field of view. This system as described by Felton et al. (1991) has one sensor pair for each nozzle with a field of view which matches the spray pattern. It also uses a single sensor which is pointing upward to measure ambient lighting conditions. There are 37 nozzles on an 18-meter spray boom, so the width of the field of view is approximately 0.5 m (20 in.). This resolution filters out any spatial information which would be useful for plant identification or crop/weed differentiation. The target application for the Detectspray system was weed control on fallow fields, however, so crop/weed differentiation was not an issue.

The performance of this vegetation detection system was evaluated by Blackshaw et al. (1998b) who used colored dye to mark the actuation of the sprayer upon vegetation detection. They reported that the detection of weeds with this system was dependent on the weed size. Canola plants needed to be at or above the three to four leaf growth stage for detection, and wheat or green foxtail needed five to six leaves to be detected. Small weeds needed to occur in densities greater than 70 plants m^{-2} for consistent detection. Crop stubble that was dense and tall impaired the ability of the sprayer to detect small weeds. These results make sense when considering the large resolution of the system. In addition, the ability of the system to detect weeds was reduced during the time periods from 70 to 80 minutes before sunset and after sunrise. However, the use of the Detectspray showed an advantage over conventional broadcast spraying by reducing the amount of herbicide applied by 19 to 80 percent with cost savings of $6 to $50 per hectare. Spraying with the Detectspray system gave weed control comparable to a conventional broadcast sprayer for 80 percent of the applications (Blackshaw et al., 1998a).

The other commercially available selective sprayer, the Patchen Weedseeker (Patchen Inc., Ukiah, CA) system uses photo-detectors to measure the intensity of the modulated light produced by light sources contained in the sensing unit (Beck, 1996). The photo-detectors measure the reflectance of the light from these modulated sources, thus minimizing the effects of sunlight variability on the sensing system. By using the light reflected from the modulated sources, the field of view is restricted in the travel direction to the approximately 0.01 m focused beamwidth of the source (Yu, 1997). In the direction perpendicular to vehicle travel, the field of view of each sensor is approximately 0.30 m for the row crop unit (Hanks and Beck, 1998). This unit uses a hood over the inter-row area to block the crop plants from the vegetation sensor with three sensors contained in each hood. The Patchen Weedseeker row crop unit thus makes no attempt to electronically distinguish the weed plants from the crop plants. The resulting system requires 1) that the operator guide the tractor and attached spraying system carefully down the row since lateral errors can lead to crop damage by the hoods and 2) that each row have at least one sensor unit.

Hanks and Beck (1998) developed the Patchen Weedseeker row crop unit and evaluated the performance of the system. They found that the system detected weeds which were "occupying more than 2 cm of the sensor FOV [field of view]." The overall reduction in volume of herbicide applied with the unit averaged from 63 to 85 percent with no observed difference in weed control.

Machine Vision Approach

In the machine vision approach, vegetation detection has been done through the use of color photography or video cameras and subsequent image analysis. In this approach, the higher green reflectance of the plants is used to determine those regions of the image which can be considered to be plants. This division of the image into plant and background regions is called segmentation and can be done through color indices or by the division of the color space by some type of calibration algorithm.

Color in color images is typically represented by three numbers representing the relative level of red, green, and blue (r,g,b) at each particular location in the image. A color index reduces these numbers to a one number representation which is defined to differentiate according to the color which best suited to the application at hand. Woebbecke et al. (1992, 1995a) developed several different color indices which mapped the three dimensional color image data to one dimension. It was determined through this work that the green chromaticity coordinate and the 2g-r-b color index provided the best contrast between the plants and the background. Meyer et al. (1998) further described a segmentation procedure which used an excess green color index where the threshold was chosen by observing where the "valley" of the excess green histogram occurred in several images.

Guyer et al. (1986) did not use color images but used one-channel gray-level images formed with a sensor which was sensitive to the whole visible and NIR broadband. The images were formed under incandescent lighting. Pixels which were more than 1.5 standard deviations above the mean intensity value for the whole image were segmented as plant pixels. Andreasen et al. (1997) segmented images by thresholding the median filtered histogram of the green chromaticity coordinate. An algorithm was developed to find the threshold which minimized the total error probability of pixel misclassification.

Detection of vegetation under controlled lighting conditions is not a difficult task. However, in field conditions under daylight, great variability results from lighting changes (Steward et al., 1999). In order for a vegetation detection system to be reliable in detecting vegetation, the sensing system must be robust to changes in lighting conditions. An environmentally adaptive segmentation algorithm (EASA) was developed by Tian and Slaughter (1998) to do plant and weed detection segmentation with robustness to lighting variations by using a "minimally supervised learning procedure." Central to the EASA was cluster analysis, which is an unsupervised learning procedure which groups together similar data points into "clusters." In the case of color segmentation, this clustering is done based on the premise that objects in the image will consist of pixels with similar color values. Segmentation with the EASA method resulted in a 26.9 to 54.3 percent increase in recovered plant pixels.

The EASA was further refined by Steward and Tian (1998) who analyzed several different classification schemes to divide up the color space. The performance of these different classifiers was measured against an image in which a person selected the regions in the image which he considered to be plants based on visual observation. Steward et al. (1999) were also able to use these algorithms to track lighting changes through image analysis as those changes occurred throughout a day.

SPECIES DISCRIMINATION

A greater challenge then vegetation detection – the discrimination of vegetation from the background – is posed by the differentiation between the crop plants and weeds. There are several ways that this problem has been addressed. In the case of the Detectspray system, the target application was for chem-fallow operations where all vegetation was considered to be a weed. The Patchen Weedseeker was used in row crops where plastic hoods were used to block the crop from the field of view of the sensors. The sensors then just detected vegetation between the rows, and once again all vegetation sensed was considered to be a weed. The prototype "smart sprayer" developed by Steward (1999) took an image across several rows of crop and used the spatial structure of the rows to eliminate them from consideration as weeds and then considered any vegetation between the rows as weeds. Shropshire and Von Bargen (1989) developed a system based on Fourier and Hadamard transforms to detect if an image of the inter-row area between two crop rows contained weeds. They reported that when NIR images were used, nearly all of the images containing weeds were correctly classified and approximately 90 percent of the images without weeds were correctly classified. With color images, only about half of the weed images were correctly classified, and all of the images without weeds were correctly classified.

These four examples illustrate one way of dealing with the issue of discriminating weeds from crops. This approach uses some knowledge about the structure of the field situation to simplify the discrimination. This is the most practical approach to this problem at present.

The general problem of discriminating between crop and weed species or classes of weed species is much more difficult, and many approaches have been taken to develop general plant species classification by machine. These approaches have commonly treated this as a pattern recognition problem. The first step in pattern recognition is to identify salient features of an object to be recognized and to quantify those features numerically. The second step is to classify the object based on the set of features for that object. This is typically done by a statistical procedure called discriminant analysis or by the use of artificial neural networks. These "classifiers" must first be trained – object classes associated with ranges of features – before classification is done (Duda and Hart, 1973). In the case of plant discrimination, three different types of features are used: spectral, spatial (object shape) and textural. It should be noted that because of resolution, the photo-detector approach uses only spectral features effectively. A machine vision approach, however, can potentially use any of the three features.

Spectral Information

The use of the magnitude of reflected light in spectral bands has been investigated as a potential method for distinguishing between types of plants. Franz et al. (1991b) investigated the use of statistical measures of the near-infrared, red, and blue wavebands of the reflectance of leaf surfaces from controlled lighting. Five measures were selected as features. When leaf orientation was not a factor, different plant species were able to be classified with only 6.25 percent error. When leaf orientation was a factor, the classification error rose to 24.2 percent. Shropshire and Glas (1992) used a series of 50 nm bandpass filters to generate a series of plant images across the 400 to 1000 nm range of CCD-based video camera. Statistical features such as the mean, standard deviation, and skewness were calculated for the intensity of leaf areas in the image for four different species of plants. It was concluded from this research that only the standard deviation of pixel intensity was useful in identifying plants which had prominent veins or other leaf features which result in variations in the intensity across the leaf. This research was conducted in diffuse daylight conditions. The camera iris was adjusted to maintain a constant exposure based on the reflectance of a gray. This method, however, did not fully compensate for lighting changes in the NIR region.

Vrindts and DeBaerdemaeker (1996, 1998) used a spectrophotometer to record high resolution spectra of weeds, crops (sugarbeets, corn, and potatoes), and soils across the ultraviolet, visible and near infrared regions (200 to 2000 nm). The average magnitudes of 10 nm bands were used as features for species classification. In this research, crops were distinguishable from weeds with very low classification errors using between 2 to 11 narrow bands as classification features. This work was done under controlled lighting conditions and with highly precise lab equipment.

Feyaert et al. (1998) described the development of an optical system which when mounted to a CCD camera will produce a spectrograph, that is, an image containing the relative light energy magnitude across the spectrum of reflected light from a scanned line. This device, in conjunction with classification software, was able to distinguish crop from weeds but with more errors than those reported by Vrindts and DeBaerdemaeker. This device, however, is more suited for practical field use than that used in the previous study.

Spatial Information

Another way to identify a plant is to use characteristics of a plant's leaf shape as pattern recognition features. A large amount of research has been documented where machine vision accomplished plant identification by leaf shape. Some of the earliest work was done by Guyer et al. (1986) who collected images of eight different plant species and calculated four spatially-based parameters from the plant shapes in the images. They found differences in the various spatially-based parameters across different species. They also found that these parameters varied with the maturity of the plant and concluded that spatially-based parameters showed potential for classifying plants of a specific species according to maturity and classifying different species within a maturity class. Further development of this work included the identification of 17 spatial features along with a knowledge-based classification approach which yielded 69 percent correct classification (Guyer et al., 1993). Zhang and Chaisattapagon (1995) used five individual leaf shape parameters to classify plants using discriminant analysis with only minor errors.

Recognizing that individual leaves occur as part of individual plants, Woebbecke et al. (1995b) developed a method for distinguishing between dicot and monocot plants based on features taken from images of individual plant canopies. Dicots were able to be distinguished from monocots with an average of 60 to 90 percent success using only one of the two best performing classification features. Variation in classification success occurred as the number of age classes varied from three to five. Dickson and Bausch (1997) performed a similar study to classify a broadleaf weed, a grassy weed, and corn by using plant shape and size features and an artificial neural network. An overall classification accuracy of 94 percent was obtained.

The use of shape to identify plants suffers from several limitations. First, long computational times are required to complete the analysis necessary to classify different plants by shape. Zhang and Chaisattapagon (1995) recognized this as a problem for realizing real-time detection. A second limitation is the fact that plant leaves do not typically occur singly in isolation, but occur as part of a plant or a clump of plants. Franz et al. (1991a) developed a method to identify partially occluded (overlapping) leaves in an image. This method was concluded to be "partially sucessful." Tian et al. (1997) used an object partition algorithm to separate overlapped leaves and then identify and locate the centers of target tomato plants. This algorithm was quite successful but was only implemented on a specific plant species at an early growth stage (cotyledon to first true leaf stage). General species identification with occlusion will necessarily be a much more difficult problem. A third limitation is the variations which occur in a plant's leaf shape as that plant grows. This issue was addressed by Woebbecke et al. (1995b) who identified "windows of time" where the canopy shape feature did not significantly change. This window of time was between 10 to 23 days after emergence for dicots and 14 to 23 days for monocots. A fourth limitation is caused by the fact that an image of a plant leaf is a two dimensional representation of a three dimensional scene. The leaf shape which shows up in an image is dependent on the relative orientation of the lighting source, the leaf, and the camera. This will cause inconsistent representation of plant leaves in the images.

Textural Information

Because weed plants do not typically occur as individual leaves or plants, it would be useful to be able to identify plants based on the color and intensity variations within the crop or weed canopy. These variations are called texture. Several studies have investigated the use of plant canopy texture as a means of identifying plants. Shearer and Holmes (1990) used texture to identify seven cultivars of nursery stock in containers. A 91 percent classification accuracy was achieved. Shearer and Holmes found that the use of color information, as well as intensity information, increased classification accuracy. This method was later extended to classification of weed canopies and soils with an overall classification accuracy of 93 percent with classical discriminant analysis (Burks et al., 1998) and 96.7 percent with a neural network (Burks et al., 1999). Zhang and Chaisattapagon (1995) investigated texture features of wheat and several broadleaf weed species by computing the Fourier spectrum of leaf images. They found that the wheat leaf texture had a highly directional nature which was different than that of the broadleaf weed species. A weed with fine texture like kochia could be differentiated from other weeds on the basis of texture features.

Meyer et al. (1998) used classical texture features to discriminate between soil, broadleafs and grasses. The boundaries of plant objects in color were determined first by using an excess green color index. Then the texture features were determined for the plant objects and soil, and discriminant analysis was used for classification. This system was able to discriminate between broadleaf and grass classes very well, but it was not able to distinguish between individual plant species very successfully.

A limitation to both shape and texture analysis is the computation time required to classify objects in the image as being a weed or a crop plant. This real-time issue has not been addressed until recently. Lee and Slaughter (1998) developed a plant recognition system using a hardware-based neural network. A hardware-based neural network is a special integrated circuit which has the neural network built with silicon and operates very fast when compared with software-based neural networks which are computer programs running on a microprocessor. Tang et al. (1999) developed a texture-based weed classification method which was designed to mimic the human visual system both at low and high levels. This novel method yielded excellent results with 100 percent classification accuracy into broadleaf and grass categories in approximately one half a second.

Another limitation of using texture for weed discrimination is that a high resolution is required to resolve on the texture to be analyzed. This requirement is particularly high for the leaf texture analysis since the texture is determined by the leaf structures which are very small. The resolution requirement for canopy texture analysis is somewhat relaxed.

Combination of Features

When we use our visual system to identify a plant, we do not use spectral, spatial, or textural features in isolation, but we use some combination of these and perhaps other features of which we are unaware. Thus in the development of robust weed sensing, a combination of the different classes of visual feature listed above may prove optimal. This was suggested in research performed by Favier et al. (1998) who used both spectral and textural features to classify eight weed species, barley, cabbage and calabrese crops species. Favier found, for the species under study, that in a case where spectral discrimination yielded poor results, discrimination by texture produced good discrimination. Blasco et al. (1998) used shape features as well as location of an object in the image to discriminate weed from lettuce which occurred in rows. When location alone was used, 75 percent of the weed plants were detected, but when spatial information was added, 85 percent of the weed plant were reported to be detected.

WEED CHARACTERISTIC ESTIMATION

The rationale for estimating local characteristics of the weed plants is based in the need to make variable-rate application decisions. If a sprayer is designed to just spot spray based on the absence or presence of weeds, then all that is needed is vegetation detection with the weed/crop discrimination under variable lighting conditions. However, if a variable rate of herbicide is to be applied, then some weed characteristics need to be estimated such as weed density or size. In addition, if weed distribution maps are to be generated, then estimates of weed densities are needed. Very little development has been done in this area of weed characteristic estimation.

Andreasen et al. (1997) investigated the use of machine vision techniques on scanned photographic color images with each pixel corresponding to a 0.123 mm x 0.123 mm surface area. This method segmented the image by using the g-chromaticity coordinate and divided the plant segments into objects representing individual plants through an iterative procedure. Both a human interactive and an automatic approach were developed for plant estimation. Blasco et al. (1998) developed a weed detection and counting methodology which generally showed good correlation with visual counting results. Nevertheless, over-counting occurred at very low weed densities and under-counting at high weed densities. Benlloch and Rodas (1998) reported on the use of a dynamic model for segmenting field images with the goal of comparing weed leaf area with total leaf area as a measure of weed density. This method used color, shape, and location information to segment the image into the three classes of crop, weeds and soil. Eighty-nine percent of the pixels classified as weed pixels were correctly classified while the remaining 11 percent were incorrectly classified crop pixels.

Steward and Tian (to appear) developed a machine vision-based method which detected the vegetation including the soybean rows and the weeds in the inter-row region. The plants in the inter-row region were isolated from the rows by spatial analysis of the scene, and an image scanning technique was used to estimate the weed density in the inter-row region for the purpose of providing sensing information for real-time control of a sprayer based on weed density. The weed density estimates were highly correlated with manual weed counts, but only because the weed counts were bimodally distributed. The mean execution time of the algorithm was 0.038 s for 0.91 m long inter-row regions.

There is plenty of room to improve upon these early efforts to automatically estimate weed density. Sources of estimate errors need to be determined like the overlap of weeds leaves causing weed plants to be under-counted. Blasco et al. (1998) suggested that weed leaf area would provide a better estimate of weed density than number of seedlings. This may be the case given the complexity of the problem.

Estimation of other weed characteristics should be explored if those characteristics are determined to be useful in determining the most efficacious herbicide rate. Herbicide label rate recommendations are often made on the basis of weed size, so weed size would be another useful parameter to estimate for variable rate application.

CONCLUSIONS

Many of the efforts documented in the literature have been in the area of generally discriminating between crop plants and weeds. While this has been very useful work in a very difficult area, it has not led us much closer to practical weed sensing. General species classification does not really fit a typical field situation. Weed species do not occur in homogeneous clusters, but in heterogeneous mixtures of species. Thus extracting features for a particular species from a typically occurring mixture of weeds with the goal of doing general classification is unrealistic. Given the challenges to accomplishing this task, perhaps a more fruitful direction of research and development would be to incorporate field structure such as row location or crop type into the weed detection system instead of trying to solve the general weed detection problem. This has been the key to success of the systems which have been commercialized and of several of the systems reported on above.

The current approaches to weed sensing are often driven by the selective or spot spraying paradigm of sensing individual weeds and applying herbicide in the presence of weeds, but not applying where weeds are absent. Current commercially-available selective sprayers using photodetector-based weed sensing are well-suited to this approach. An alternative paradigm is that of doing variable rate post-emergence application based on weed characteristics like weed density and plant size. Photo-detector-based weed sensing is not so well-suited for this approach because of its low resolution and therefore with limited potential for measuring weed characteristics. Machine vision-based weed detection is more suitable for this approach because of its access to spectral, spatial, and textural sources of information. Operating under this paradigm does not require the detection of individual plants but instead requires estimation of weed characteristics as they vary spatially in the crop field.

Much of the research in this area has been with devices which are not practical for in-field use. Another useful area of research would be to investigate the use of sensors that could practically be used in the field to see how their performance affects the accuracy of weed detection as compared with results obtained in the laboratory. In addition, the performance of these sensors and systems need to be evaluated under the varying lighting conditions experienced in outdoor field conditions.

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